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13. ABSTRACT (Maximum 200 words)

Cognitech researchers have worked with Dr. Brent Ellerbroek of Philips Laboratory on the task of restoring noisy, blurry images which arise in aero-optic metrology. Cognitech's TV and MTV (recently developed by Dr. Rudin) algorithms were applied to Philips supplied data using experimentally obtained point spread functions and various nonlinear noise models. The algorithms were speeded up using an implicit method which allowed the constraints to be enforced for large time marching steps. The results, successfully applied to real images, are displayed.

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Cognitech, Inc. has used its state-of-the-art algorithms to restore noisy blurry images supplied to us by Dr. Brent Ellerbroek of Philips Laboratory.

The goal is to reconstruct real images which arise in aero-optic metrology.

Cognitech's technique is based on the use of nonlinear partial differential equations and multiscale analysis. Specifically we are given a noisy blurry image in the form

$$u_0(x,y) = (Au)(x,y) + n(x,y) \quad \text{(additive noise)} \tag{1}$$

$$u_0(x,y) = [(Au)(x,y)][n(x,y)] \quad \text{(multiplicative noise)} \tag{2}$$

Other models of multiplicative noise and speckel noise have also been tried.

Here A is a linear integral operator whose point spread function is given experimentally, and statistics of the noise-mean and variance- are estimated.

Our original method was just to minimize the total variation (TV) of the image subject to the constraints induced by the models (1), (2) (or otherwise). See [1,2,3] for further discussion.

Recently Dr. Rudin, developed an important modification of this algorithm which appears to be even less invasive than the TV based restoration while still finding features in blurry, noisy images. Namely, one minimizes the quantity:

$$MTV(u) = \int_1 \frac{|\nabla u|}{|j_\delta * \nabla u|} dx. \tag{3}$$

Here $|\nabla u| = \sqrt{u_x^2 + u_y^2}$, $j_\delta = j\left(\frac{x-y}{\delta}\right)$ for $\delta > 0$ where j is a positive smoothing kernel of mass one and $*$ denotes convolution. Various values of δ are chosen, depending on the desired level of sharpness. Thus this method is denoted multiscale total variation regularization.

We also intend to use some of the newer restoration algorithms which we developed in [4] which involve free local constraints in future work in this area.

An additional new idea came in speeding up the restoration procedure by making the algorithm fully implicit, including an implicit treatment of the constraints. We wish to update an algorithm of the form:

$$\begin{aligned} u_{ij}^{n+1} = u_{ij}^n + CFL[&a_{i+\frac{1}{2}j}^n \Delta_+^x u_{ij}^n + a_{i-\frac{1}{2}j}^n \Delta_-^y u_{ij}^n \\ &a_{i,j+\frac{1}{2}}^n \Delta_+^y u_{ij}^n + a_{i,j-\frac{1}{2}}^n \Delta_-^y u_{ij}^n] \\ &+ \lambda \ (\text{constraint})^n. \end{aligned} \tag{4}$$

Here λ is a Lagrange multiplier, CFL is the time step/space step ratio, the term (constraint) comes from the Euler-Lagrange equations for the statistical and blurring constraints. Also

the $a^n_{i,j}$ are nonlinear functions of (u^n), but they are always nonnegative. Our first observation is that we can increase the CFL to an arbitrary level, for $\lambda = 0$, by simply replacing the terms $\Delta^{x,y}_{\pm} u^n_{ij}$ by $\Delta^{x,y}_{\pm} u^{n+1}_{ij}$. The result is a linear system which is uniformly diagonally dominant and block tridiagonal, thus it is easily inverted by e.g. approximate factorization. However λ has to be chosen so that a certain nonlinear constraint is satisfied.

We do this as follows: We wish to solve

$$[I + L]u^{n+1} = u^n + \lambda\,(\text{constraint})^n \tag{5}$$

where u^{n+1} satisfies a certain nonlinear constraint. We compute

$$z^{n+1} = (I + L)^{-1} u^n \tag{6a}$$

$$w^{n+1} = (1 + L)^{-1}\,(\text{constraint})^n. \tag{6b}$$

Then $u^{n+1} = z^{n+1} + \lambda w^{n+1}$.

We finally choose λ so that the nonlinear equation enforcing the constraint is satisfied.

A key step in our restoration procedure, suggested by L. Rudin, is to use it iteratively with our multiscale segmentation algorithm using the method originating in the work of our consultants, Professor J.-M. Morel and improved significantly at Cognitech by Rudin and Nordby, in collaboration with our French consultants [5,6].

We now describe our results, all done on our HP 735 computers, using a few minutes of computing time, at most. Figure (1a) shows the original degraded image (SeaSat 119a), while (1b) shows our restoration using TV regularization with an additive noise model. Figure (1c) shows the restoration using MTV, assuming a multiplicative noise model iterated together with our multiscale segmentation through which the constraints were enforced locally.

Figure (2a) shows the original degraded image (SeaSat 123a). In figure (2b) we use our TV restoration assuming additive noise, while figure (2c) displays the result using MTV restoration, again assuming additive noise.

Figure (3a) shows the original degraded image (SeaSat 081a) while figure (3b) shows the restored image using MTV, iterated segmentation - restoration, assuming a multiplicative noise model.

Figures (4a,b) show the analogous sequence for image SeaSat 082a.

Figures (5ab) show the the analogous sequence for SeaSat 087a, while figure (5c) shows the result of combining this with TV restoration.

We conclude that our approach is a very promising line of attack for the restoration of images of this type. Other restoration models will be used as well as constraints based on a speckel noise assumption.

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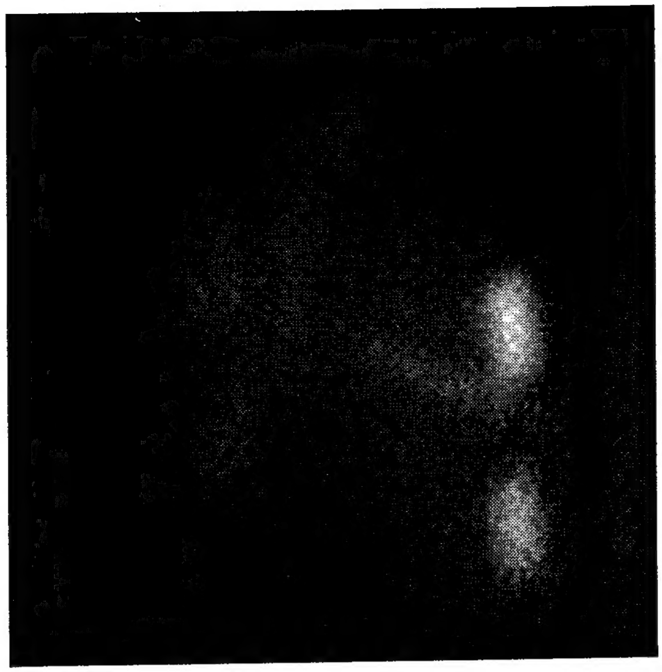
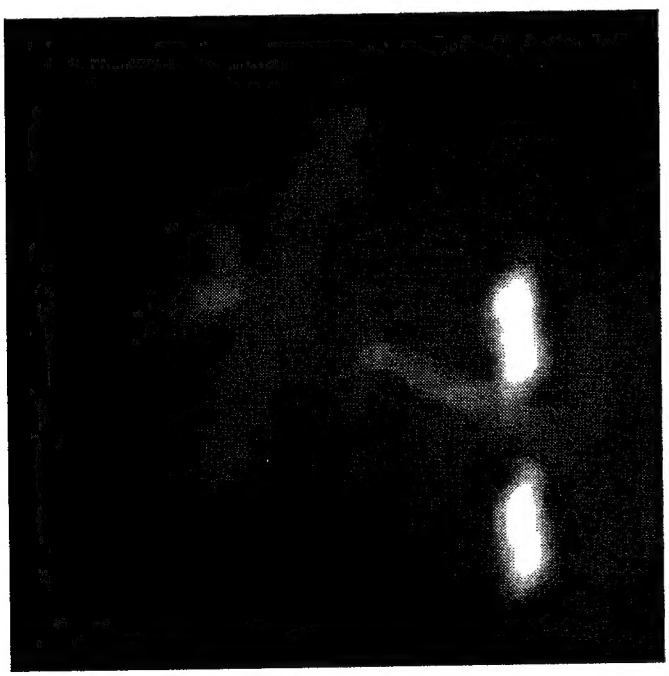


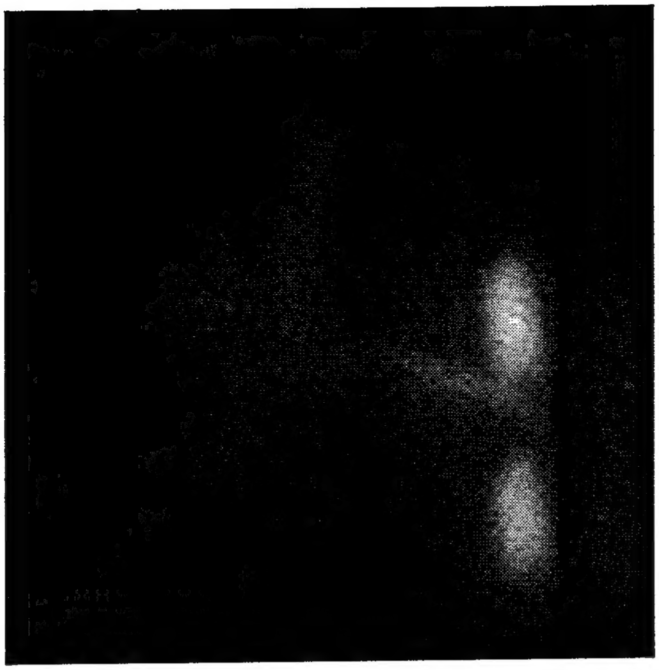
a) Original Image (Seasat 119a)



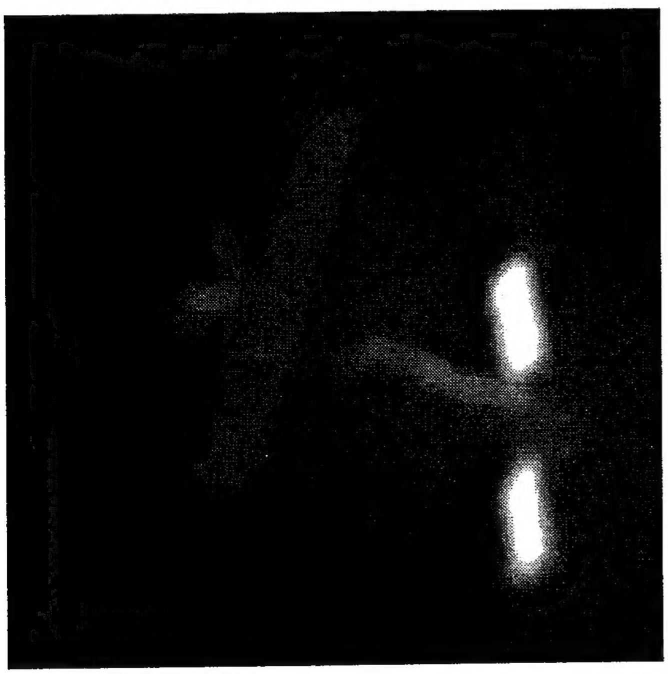
b) Restoration of Original Image using Total Variation, assuming additive noise

c) Restoration of Original Image using Multiscale Total Variation and Segmentation, assuming multiplicative noise

Figure 1



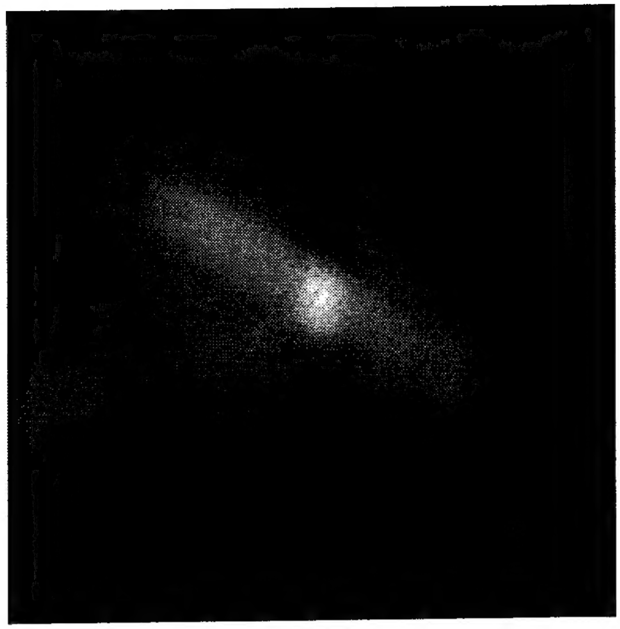
a) Original Image (Seasat 123a)



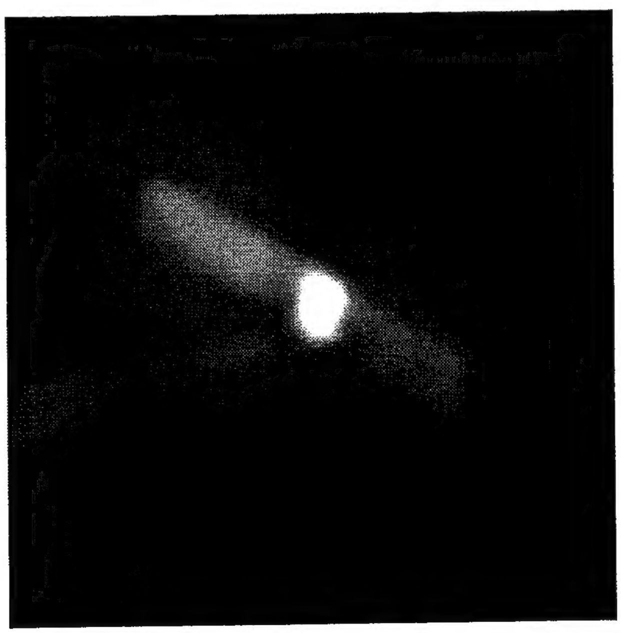
b) Restoration of Original Image using Total Variation, assuming additive noise

c) Restoration of Original Image using Multiscale Total Variation, assuming additive noise

Figure 2

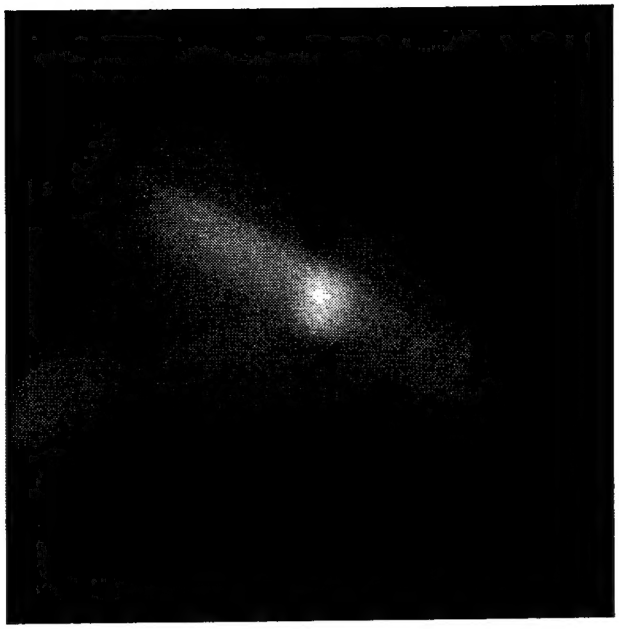


a) Original Image (Seasat 081a)

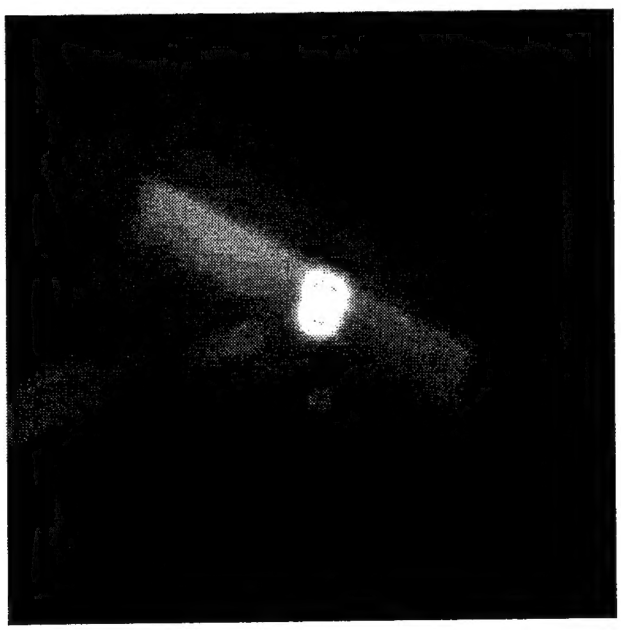


b) Restoration of Original Image using Multiscale Total Variation and Segmentation, assuming multiplicative noise

Figure 3

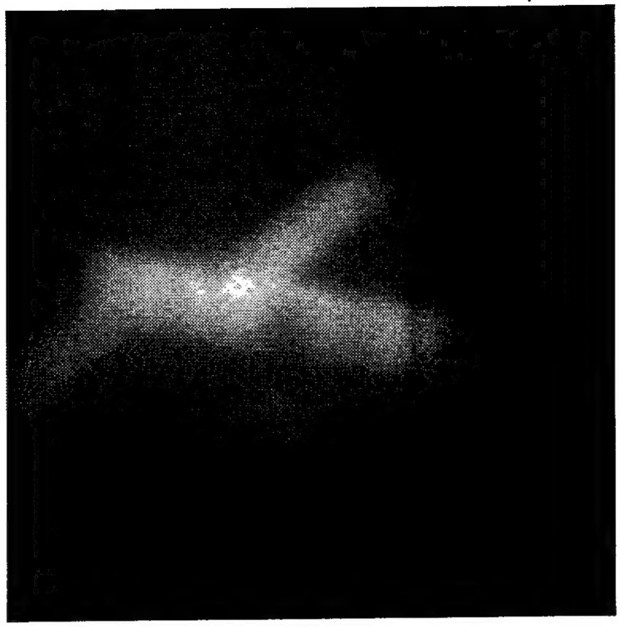


a) Original Image (Seasat 082a)

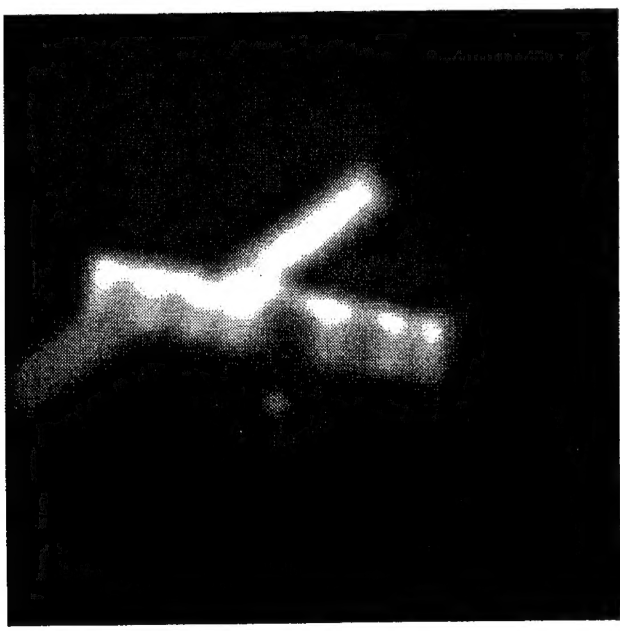


b) Restoration of Original Image using Multiscale Total Variation and Segmentation, assuming multiplicative noise

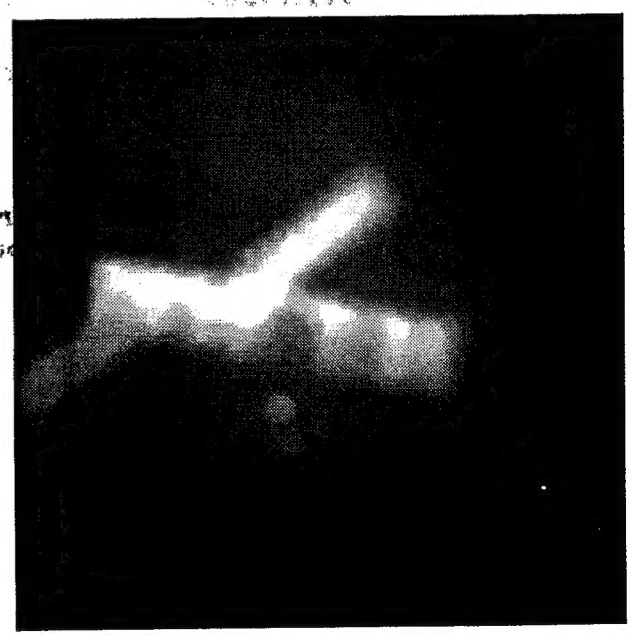
Figure 4



a) Original Image (Seasat 087a)



b) Restoration of Original Image using Multiscale Total Variation and Segmentation, assuming multiplicative noise



c) Restoration of Original Image using Total Variation, Multiscale Total Variation, and Segmentation, assuming multiplicative noise

Figure 5